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Wind speed prediction using LSTM and ARIMA time series analysis models: A case study of Gelibolu

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Abstract

Wind energy stands out as a prominent renewable energy source, characterized by its high efficiency, feasibility, and wide applicability. Nonetheless, the integration of wind energy into the electrical system encounters significant obstacles due to the unpredictability and variability of wind speed. Accurate wind speed prediction is essential for estimating the short-, medium-, and long-term power output of wind turbines. Various methodologies and models exist for wind speed time series prediction. This research paper proposes a combination of two approaches to enhance forecasting accuracy: deep learning, particularly Long Short-Term Memory (LSTM), and the Autoregressive Integrated Moving Average (ARIMA) model. LSTM, by retaining patterns over longer periods, improves prediction rates. Meanwhile, the ARIMA model enhances the likelihood of staying within predefined boundaries. The study utilizes daily average wind speed data from the Gelibolu district of Çanakkale province spanning 2014 to 2021. Evaluation using the root mean square error (RMSE) shows the superior forecast accuracy of the LSTM model compared to ARIMA. The LSTM model achieved an RMSE of 6.3% and a mean absolute error of 16.67%. These results indicate the potential utility of the proposed approach in wind speed forecasting, offering performance comparable to or exceeding other studies in the literature.

1. Introduction

In our modern era, energy consumption spans various sectors, predominantly reliant on non-renewable resources, which are depleting steadily [1]. Traditional methods for energy generation predominantly rely on non-renewable resources, exacerbating environmental concerns and energy security issues [2]. The effectiveness of wind energy systems is directly contingent upon wind speed, making accurate wind speed prediction imperative for efficient wind power generation [3]. While statistical methods have traditionally been employed for wind speed estimation, their adequacy may be compromised due to the inherently chaotic nature of wind patterns [4]. Consequently, artificial intelligence algorithms have emerged as viable alternatives for wind speed prediction [5]. Artificial intelligence (AI) technologies offer promising solutions [6] to address these challenges by optimizing energy generation and consumption, particularly in the context of renewable energy sources such as wind power [7]. Numerous studies in the literature highlight the potential of AI algorithms in optimizing wind energy systems, improving efficiency, and overcoming the limitations of traditional statistical methods.

Akbulut and Kemal [8] conducted a study on the effectiveness of deep learning and machine learning models in financial market forecasting. Their research revealed that the Long Short-Term Memory (LSTM) model outperforms the Instance-Based Learning k-Nearest Neighbors method in terms of error rate. The investigation encompassed an analysis of the correlation between commodity and exchange rates as well as stock market indices of developing countries. The findings suggest that the LSTM model exhibits efficiency as a predictive tool. Consequently, it is expected that this model could offer valuable assistance to investors in anticipating market trends.

Eşsiz [9] delves into short-term power prediction by utilizing daily wind data from the Belen region. The study employs analyses employing a radial-basis regressor method and the harmony search algorithm. Results indicate that predictions generated with the harmony search algorithm exhibit fewer features and errors, leading to a notable 7% enhancement in RMSE. These findings highlight the efficacy of the harmony search algorithm in wind power prediction.

Balcı et al. [10] introduce a hybrid technique for estimating hourly wind speed data collected above 50 m in Balıkesir city. This method combines multilayer perceptions (MLP) with complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and ensemble empirical mode decomposition (EEMD).

According to Balti et al. [11], in their quest to understand the causes of drought, the study explored the predictive abilities of three different methods—ARIMA, Prophet, and LSTM—using meteorological variables such as the standardized precipitation evapotranspiration index (SPEI). The study's results indicated that although the ARIMA model performed better than the Prophet model, the LSTM model outperformed both. This emphasizes the reliability and accuracy of the LSTM model in identifying the underlying causes of drought.

Baykal et al. [12] undertook a study to forecast meteorological drought in Isparta province over the next decade employing the LSTM method. Their research unveiled a parallel declining trend in precipitation and DEM series, with severe droughts noted between 1982 and 2011. The study proposes that extending the time interval of precipitation data generated by the LSTM method could aid in long-term water resource planning and the execution of essential measures.

Canıtez and Savaş [13] conducted a study comparing feature-based LSTM and ARIMA methods for predicting the market value of cryptocurrency, focusing specifically on Bitcoin. The study utilized 10,309 real-time data points. Both ARIMA and LSTM techniques were employed to generate predictions. The results revealed that the MAPE values of both approaches fell within the "very good" range. However, upon comparison, it was observed that the ARIMA method produced superior outcomes, suggesting that the behavior of Bitcoin prices is more accurately captured by the ARIMA approach.

Dave et al. [14] conducted a study focusing on forecasting Indonesia exports using a hybrid ARIMA-LSTM model. Within this study, they assessed a hybrid model (LSTM-ARIMA) to establish an integrated machine learning model for wind speed prediction. The findings of their research revealed that the hybrid model exhibited the lowest error metrics compared to all other models examined. This underscores the hybrid model's superior accuracy and reliability in wind speed prediction.

Demirtop and Işık [15] introduced a novel methodology utilizing artificial neural networks (ANNs) to enhance wind energy efficiency. They utilized a dataset comprising temperature, pressure, humidity, and wind speed data collected from Bozcaada, Çanakkale. ANN models were trained using both WEKA and MATLAB platforms. Among the methods evaluated, the Levenberg-Marquardt algorithm demonstrated superior accuracy, with MATLAB exhibiting better performance than WEKA. The authors advocate for further research utilizing larger datasets and diverse ANN architectures to validate the applicability of ANNs in forecasting wind energy efficiency.

Devi et al. [16] utilized the extended Long Short-Term Memory network-enhanced Forgetting Gate network (LSTM-EFG) model for wind energy prediction. Their study involved training the model on sub-series data obtained through ensemble empirical mode decomposition (EEMD) and refining it with the cuckoo search optimization technique (CSO). The research demonstrated enhanced prediction accuracy, surpassing traditional forecasting approaches.

Elsaraiti and Merabet [17] conducted a comparative analysis of Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Autoregressive Integrated Moving Average (ARIMA), and Long Short-Term Memory (LSTM) - a variant of RNN - to determine the optimal method for time series forecasting. The findings revealed that the LSTM approach outperformed the ARIMA method in forecast accuracy. These results underscore the superior predictive capabilities of the LSTM method, which yields more precise forecasts with fewer errors.

Erden [18] conducted a comparison between ARIMA and deep learning models for forecasting Borsa Istanbul's EREGL stock, taking into account the nonlinear and complex nature of financial time series data. Through data preprocessing, feature extraction, and analysis of different time periods, prediction performance was enhanced. The Recurrent Neural Network (RNN) algorithm exhibited an impressive accuracy rate of 93% in this context.

Ji et al. [19], a model named ARIMA-CNN-LSTM was developed to predict the price of carbon futures. In this model, long-term relationships in the data are captured by LSTM, hierarchical data structures are captured by CNN, and linear characteristics are captured by ARIMA. The findings of the study demonstrate that the ARIMA-CNN-LSTM model outperforms the benchmark model in terms of prediction accuracy. This outcome illustrates that the ARIMA-CNN-LSTM model provides a more reliable and accurate method for predicting the price of carbon futures.

Kamber et al. [20] conducted an analysis of hourly electricity data within an LSTM-based artificial neural network (ANN) framework using Spain's electricity data for the years 2015-2016, and compared it with ARIMA results. Through this comparison, both forecasting models exhibited similar performance. These findings indicate that both LSTM and ARIMA models are equally effective for hourly electricity forecasting.

Liu et al. [21] proposed a Seasonal Auto Regression Integrated Moving Average (SARIMA) model for forecasting hourly observed wind speeds in the onshore/offshore area of Scotland. The model was trained using three wind speed time series obtained from various heights of a coastal measuring mast designed for servicing an offshore wind turbine. Test results indicated that, compared to the GRU and LSTM models, the SARIMA model produced more reliable and accurate predictions. This outcome underscores the SARIMA model's utility as a valuable tool for forecasting offshore wind speed time series.

Othman [22] utilized Bayesian optimization to optimize various parameters, including the number of biLSTM layers and units. Among the models evaluated, the one utilizing SGDM exhibited the highest performance, as determined by Spearman's Rank Correlation (r). The study employed three distinct algorithms—SGDM, ADAM, and RMSprop—to train deep CNN-biLSTM models. Ultimately, the study highlighted the effectiveness of the CNN model with LSTM in replicating time series data.

Sevinç and Buket [23] utilized temperature data from the Solhan district of Bingöl province to evaluate the forecasting capabilities of LSTM and ARIMA models. The findings indicated that the LSTM model achieved a mean error (MAE) of 0.73 °C, while the ARIMA model's MAE was 0.76 °C. These results suggest that both models produce forecasts closely aligned with the actual values, indicating their comparable performance. The comparison underscores the excellent accuracy of both models, as evidenced by the achieved MAE values.

Shao et al. [24] focused on the development of an LSTM neural network model and the optimization of hyperparameters for wind speed prediction, which is a significant topic of interest. The study's findings indicated that the FWA-optimized LSTM model outperformed alternative regression techniques commonly employed for wind speed prediction.

Wang and Wang [25] proposed a mixed model incorporating Empirical Mode Decomposition (EMD), Long Short-Term Memory (LSTM), and Autoregressive Integrated Moving Average (ARIMA) for forecasting monthly precipitation. The study demonstrated the superior forecasting performance of this model compared to various combination models and single models, including EMD-LSTM, EEMD-LSTM, EEMD-ARIMA, among others. Additionally, the model exhibited a high level of confidence in the predicted precipitation results.

Zhang et al. [26] aimed to identify the most effective model for predicting the prevalence of hand, foot, and mouth disease (HFMD) in Ningbo. The study evaluated two forecasting models, ARIMA and LSTM. According to the findings, the multivariate LSTM model provided the best fit for the daily incidence of HFMD in Ningbo among the four models tested. This multivariate LSTM model incorporates factors such as precipitation, humidity, and air temperature to enhance the accuracy of HFMD incidence prediction.

Zhang et al. [27] conducted a study yielding significant results demonstrating the efficacy of LSTM-based approaches in time series forecasting. The findings indicate that LSTM-based techniques outperform hybrid and CNN-based techniques, attributed to their superior ability to capture long-term dependencies in time series data. Notably, the study's second case study achieves longer-term forecasts, with deep learning-based techniques outperforming the ARIMA method and exhibiting similar performance among themselves.

Zhao et al. [28] employed ARIMA, LSTM, and various machine learning models for demand forecasting using sales data from a company in the retail sector. The CRISP-DM methodology was adopted, encompassing data preprocessing, time series analysis, and model evaluation stages. According to the findings, machine learning models exhibited superior performance compared to ARIMA and LSTM models. Specifically, within the ARIMA models, the SARIMAX model outperformed both ARIMA and SARIMA models, attributed to its utilization of independent variables.

This study contributes to the literature by comparing the effectiveness of deep learning models such as LSTM with statistical analysis-based ARIMA models in predicting future wind speeds using current meteorological data from a specific region in Türkiye. Particularly, it sheds light on the performance of ARIMA alongside LSTM, emphasizing the role of both methodologies in wind speed prediction. The findings underscore the potential of deep learning techniques, represented by LSTM, in outperforming traditional statistical approaches like ARIMA in wind speed forecasting. Moreover, by evaluating various performance metrics of different model approaches, this research aims to provide valuable insights into their prediction accuracy and implications for practical applications. Additionally, the utilization of ARIMA in conjunction with LSTM offers a comprehensive understanding of the strengths and limitations of both approaches, contributing to the advancement of knowledge in the field of renewable energy forecasting.

2. Method

2.1. Dataset

Our research area is located in the Gelibolu district, situated between the Dardanelles and Saroz Gulf in the Marmara Region of northwestern Türkiye. This area exhibits seasonal transition characteristics, reflecting the typical features of the Mediterranean climate. Due to its northern latitude, winter temperatures are relatively lower, with August experiencing a maximum temperature of +35.8 °C and February reaching a minimum of -4.2 °C. Throughout the year, the average temperature and humidity are 14.7°C and 72.6%, respectively. Additionally, the region is characterized by consistent windy conditions throughout the year, distinguishing it from other locations [29].

In this study, we employed a dataset encompassing daily average wind speed records spanning from the years 2014 to 2021 for the Gelibolu district of Çanakkale province [30]. The dataset comprises 2908 data points, each representing a single day, with the wind speed measurements ranging from a minimum of 2.88 km/h to a maximum of 60.48 km/h. The graph presented in Figure 1 illustrates the distribution of these data points, with wind speed (measured in km/h) plotted on the vertical axis and the total number of days (data points) on the horizontal axis.

The average wind speed across the dataset was calculated to be 15.51 km/h. This comprehensive dataset allows for a detailed analysis of the wind speed patterns and variations observed in the Gelibolu district over the specified time period. Such insights are crucial for understanding the local wind climate dynamics, which in turn can inform various applications, including renewable energy resource assessment, environmental monitoring, and infrastructure planning.

Analyzing the graph for the region by years in Figure 2, it is evident that the average wind speed exhibits variations over the years. Specifically, the data indicates that the average wind speed was at its lowest in 2014 and reached its peak in 2018. This observation suggests temporal fluctuations in wind speed patterns within the Gelibolu district over the specified time period. Such insights into the interannual variability of wind speeds are valuable for understanding long-term trends and can inform decision-making processes in various sectors, including energy, agriculture, and infrastructure planning [5].

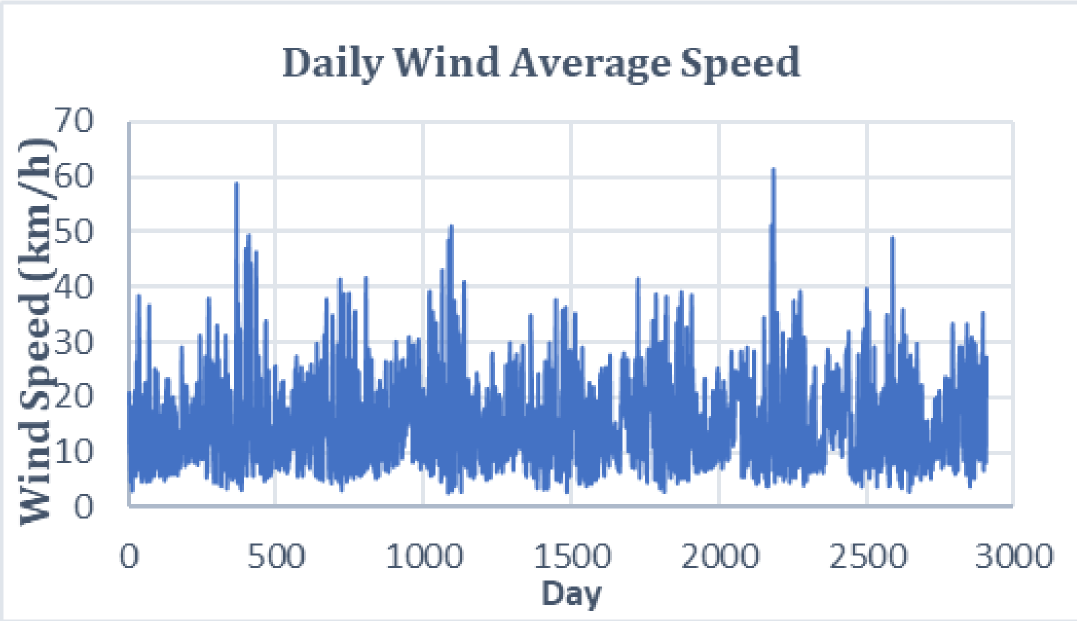


Figure 1. Daily average wind speed of the region (km/h).

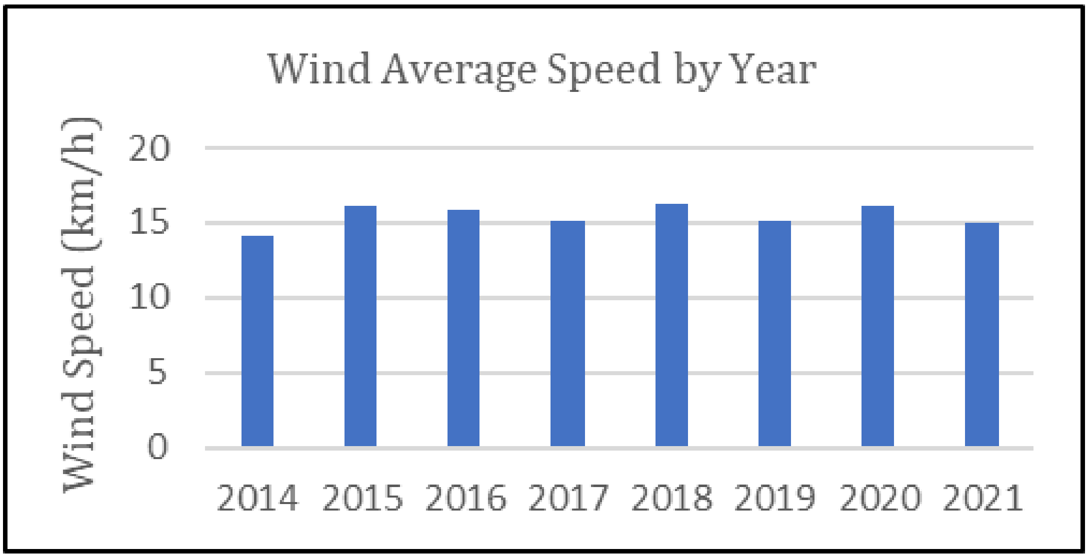


Figure 2. Wind mean speed according to years in the region.

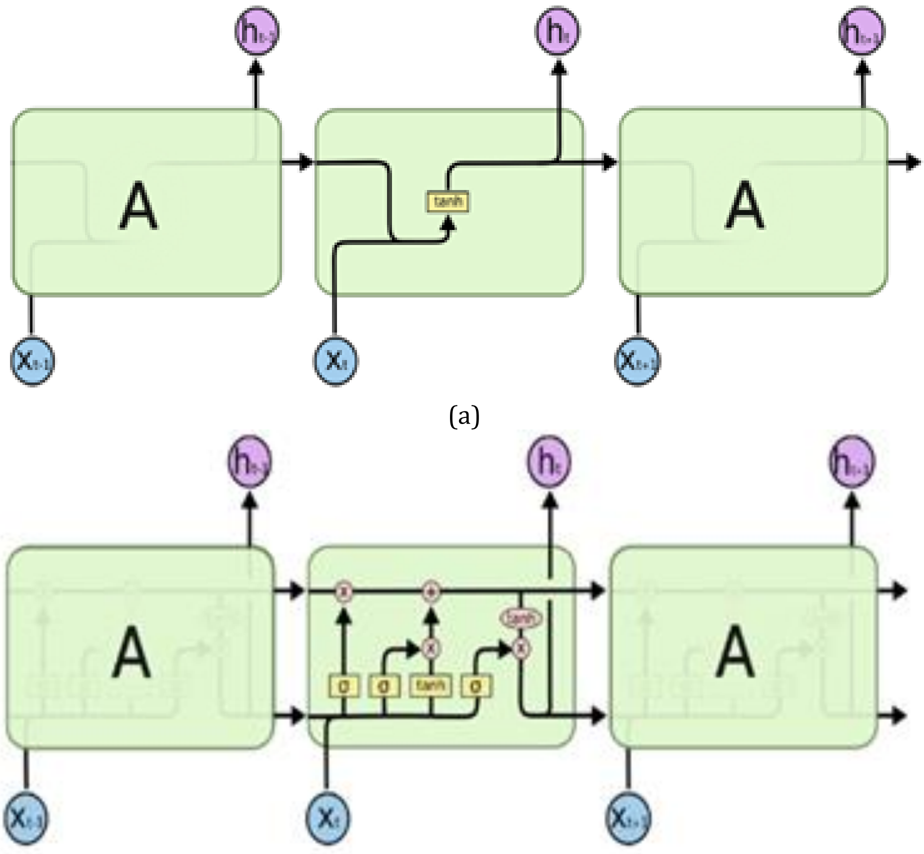
2.2. Analysis models used

2.2.1. Long-short term memory (LSTM)

Recurrent neural networks, including long short-term memory models (LSTMs), are well-suited for processing temporal data due to their ability to capture long-term dependencies [31]. LSTMs are particularly advantageous in applications such as speech recognition and natural language processing, where recognizing patterns over extended sequences is essential [32]. Key to the effectiveness of LSTMs is their utilization of cell states to store information across time [33]. The cell state serves as a memory unit within the LSTM, regulating the flow of information into and out of the network at each time step through controlled updates [34]. This mechanism enables LSTMs to effectively retain and utilize contextual information over extended sequences, facilitating accurate predictions and analysis of temporal data.

Recurrent neural networks, such as long short-term memory models (LSTMs), are adept at handling temporal data due to their capability to discern long-term patterns [35]. LSTMs are particularly favored in applications like speech recognition and natural language processing owing to their ability to recognize extended sequences effectively [36]. LSTMs utilize cell states to retain information across time, regulating the flow of data throughout the network. This mechanism enables LSTMs to maintain and utilize contextual information over prolonged sequences, thereby facilitating accurate predictions and analysis of temporal data [37].

LSTM networks address the vanishing/exploding gradient problem by employing gates and a well-defined memory cell. These gates regulate the flow of information into and out of the cell. The input gate determines the amount of data from the previous layer that is stored in the cell. The output gate controls how much information about the cell's state is passed to the next layer. The forget gate manages the retention of data stored in the cell. This mechanism enables LSTM networks to effectively learn over multiple time steps and capture long-term dependencies (Figure 3).



(a)

(b)

Figure 3. LSTM and RNN recurrent modules. (a) an RNN's recurrent module has one component. This is the neural network stack. (b) An LSTM's recurrent module has four interacting layers [38].

The design depicts the LSTM with three layers stacked, as illustrated in Figure 4. LSTM is a type of artificial neural network utilized for capturing long and short-term dependencies. The three-layered structure indicates a deep architecture, enabling the network to learn more complex relationships.

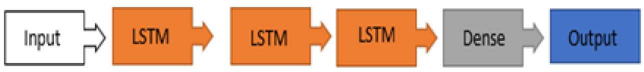


Figure 4. Long short-term memory neural network (LSTM) design with three layers stacked.

In Table 1, the LSTM model can be trained and predicted in three steps as outlined below:

1. Data Preprocessing: The data undergoes preprocessing where it is rescaled and normalized to the range of 0 to 1. This step is crucial as LSTM models are sensitive to the scale of the input data.

2. Model Parameter Determination: The univariate and multivariate LSTM time steps are adjusted to predict the wind speed for the following day using data from the preceding 7/30/60/180 days. Each LSTM layer in the three-layer stacked LSTM structure consists of a hidden layer that is tailored for the LSTM model. Alternative optimization functions such as Stochastic Gradient Descent (SGD), Adaptive Moment Estimation (Adam), and Root Mean Square Prop (RMSProp) are considered.

3. Model Training: Training is conducted over 200, 250, 500, and 1000 epochs for each learning procedure. The least Root Mean Square Error (RMSE) of each batch of 125 epochs is utilized to determine the best-suited model. The starting learning rate is set at 0.005.

Table 1. Parameters used in the LSTM structure.

Time Stages	7/30/60/180 days
Neurons	4/8/16/32/64/72/128/256
Optimization Functions	Adam/SGD/RMSProp
Number of Data Iterations (Epoch)	200/250/500/1000
First Learning Rate	0.005
Study the Rate Schedule:	fragmented
Learn Rate Decline Time:	125
Factor for Learning Rate Drop:	0.2

2.2.2. Autoregressive integrated moving average (ARIMA)

Autoregressive Integrated Moving Average, abbreviated as ARIMA, is a statistical model commonly employed for time series data forecasting. ARIMA models are based on the premise that data can be represented as a linear combination of historical values, errors, and moving averages. These models are widely utilized for predicting variables such as wind speeds, solar radiation levels, stock prices, interest rates, and inflation. ARIMA modeling enables analysts to make accurate forecasts and projections based on historical patterns and trends observed in the data [39].

ARIMA models are employed for predicting time series data using a methodology known as the Box-Jenkins method [40], which consists of four stages:

1. Identification: In this stage, the order of the ARIMA model is determined. The order is defined by the number of autoregressive terms (p), the number of differences to be taken (d), and the number of moving average terms (q) [40].
2. Estimation: Model parameters are estimated using the method of maximum likelihood estimation [40].
3. Diagnostic check: A diagnostic check is performed on the ARIMA model to ensure that the residuals exhibit white noise behavior and that the model adequately captures the data [40].
4. Forecasting: Future values of the time series are predicted using the estimated parameters of the ARIMA model [40].

ARIMA models are particularly effective for predicting time series data and are commonly utilized in short-term forecasting tasks [40]. The notation ARIMA(p,d,q) is used to denote an ARIMA model, where:

- p represents the autoregressive degree (AR),
- d represents the degree of differencing (I),
- q represents the moving average (MA).

In ARIMA models, the autoregressive parameters represent the lags of the differenced time series, while the moving average terms account for the forecast error delays [41]. If the time series is non-stationary (or seasonal), differencing is applied to make it stationary. The resulting integrated series is then modeled using ARIMA (p, d, q). In this notation, p, d, and q denote the quantities of autoregressive terms, lagged forecast errors, and non-seasonal differences, respectively. Equation 1 provides the general ARIMA formula.

$$y_t = c + \sum_{i=1}^{p} \phi_m y_{t-i} + \sum_{j=0}^{q} \theta_n e_{t-j} \tag{1}$$

In Equation 1 ϕ_m autoregression coefficient, ϕ_m y_(t-i) autoregression lags (at degree p), θ_n moving average parameter, e_(t-q) moving average errors (of order q) and c is the constant term [40].

The linear connection between the time series' lag values and the error term determines the degree of autoregression [40]. The AR(p) model here is as in Equation 2.

$$y_i = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + c \tag{2}$$

The moving average degree relies on a weighted moving average of error values as outlined in the literature [40]. Equation 3 provides a general representation of the MA(q) model.

$$y_i = \theta_0 e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{3}$$

The fusion of autoregressive (AR) and moving average (MA) methodologies constitutes the basis of the ARMA (p,q) approach [40]. Equation 4 presents the autoregressive moving average (ARMA) model.

$$y_i = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_0 e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{4}$$

3. Experimental study and findings

3.1. Data analysis

The training dataset comprised data spanning from January to December 2016, while the test dataset was selected from December 2020 onwards [30]. To forecast daily wind speed data, ARIMA and LSTM models were trained using the training dataset, both with and without incorporating external meteorological factors [16]. Three index metrics were identified to evaluate the models' performance. The primary performance metric for comparing predicted values with actual values is the RMSE [42]. It is calculated using the Equation 5.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_i - X_i')^2}{n}} \tag{5}$$

The mean absolute error (MAE) [42], which is the second performance metric, is defined as Equation 6.

$$MAE = \frac{\sum_{i=1}^{n} | X_i - X_i' |}{n} \tag{6}$$

The third performance metric is relative overall conformance, quantified by the mean absolute percentage error (MAPE) [42]. The formula for calculating this metric is presented in Equation 7.

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|X_i - X_i'|}{X_i} \times 100}{n} \tag{7}$$

The RMSE, MAE, and MAPE measures are commonly employed to assess the performance of models in time series forecasting, including both ARIMA and LSTM models [16]. RMSE is particularly suitable for evaluating the accuracy of the forecast, as it provides a measure of the average magnitude of the errors between predicted and actual values [43]. On the other hand, MAE is preferred for evaluating the consistency of the forecast, as it calculates the average absolute errors between predicted and actual values. Additionally, MAPE can be utilized to evaluate both accuracy and consistency, as it expresses the average percentage difference between predicted and actual values, providing insights into the relative performance of the models across different time series [42].

3.2. Forecast verification

The real-world environment is characterized by instability and frequent sudden changes, which can significantly impact time series data such as wind speed. A forecasting model for wind speed must be capable of adapting rapidly to these dynamic changes in order to remain effective [44]. Therefore, it is imperative for a wind speed forecasting model to be flexible and responsive to sudden fluctuations in environmental conditions. Only by incorporating adaptability into the forecasting model can it effectively account for the unpredictable nature of the environment and provide accurate forecasts even in the face of rapid changes [3].

In this study, a rolling prediction scenario, also known as forward walking model validation, is utilized. In this scenario, the test dataset's time steps are advanced incrementally. At each step, the observed value from the test set is used to forecast the subsequent time step using the model. This process simulates real-world conditions, where fresh daily wind speed data is continuously collected and utilized to predict wind speed for the following day. By employing this approach, the model's performance can be evaluated in a dynamic and evolving context, mirroring the conditions under which it would be utilized in practice [45].

The two parameters commonly used to forecast wind speed are the MAE and the RMSE, which assess the accuracy and precision of the models, respectively. The MAE measures the average absolute difference between the expected and actual values. On the other hand, the RMSE computes the square root of the mean square difference between the actual and predicted values, providing a measure of the overall deviation between them [42]. These metrics are essential for evaluating the performance of wind speed forecasting models and assessing their effectiveness in providing accurate predictions.

In this study, both an LSTM model and several sequential ARIMA models are employed for wind speed prediction. Through the utilization of a rolling forecast scenario, the LSTM model is demonstrated to outperform the other models in terms of accuracy and flexibility. This superiority can be attributed to the LSTM model's ability to retain and leverage past data over prolonged periods, allowing it to make more informed forecasts for future time steps.

RMSE represents the square root of the mean square of all errors, providing a comprehensive measure of error. Widely acknowledged as a superior error metric for numerical predictions, RMSE is commonly employed in regression tasks across both statistical and machine learning domains [42].

The RMSE quantifies the difference between expected and actual values, with a larger RMSE indicating greater deviations. A notable property of the RMSE is that squaring the errors assigns significantly more weight to larger errors. Therefore, a mistake with a value of 10 is considered 100 times more impactful than a mistake with a value of 1 in the context of RMSE calculation. This weighting mechanism emphasizes the significance of larger errors in the overall evaluation of predictive accuracy. While it depends on size, RMSE is a useful metric for assessing accuracy. As a result, it can only be applied to compare prediction errors within a variable, not across variables, between models or model configurations [42].

The MAE measures the average discrepancy between expected and actual values, serving as a metric for error assessment. It represents the mean absolute difference between these values. The MAE provides insight into the average magnitude of errors expected from the forecast. Unlike RMSE, the inaccuracy scales linearly with MAE, meaning that each error contributes equally to the overall measure. Consequently, a deviation of 10 is ten times more significant than a deviation of 1 when considering MAE calculation [42].

4. Results

4.1. Prediction model ARIMA

The research period aimed at selecting the ARIMA model structure encompasses data gathered by the General Directorate of Meteorology spanning from 2014 to 2021 [30]. Out of a total of 2500 daily average time series wind speed data points, the initial 2400 points were employed in constructing the models. Subsequently, prediction and performance evaluation were conducted using the remaining 100 data points. The determination of the P and q orders was facilitated through an analysis of the autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs.

In this study, the conventional ARIMA modeling approach is applied to forecast wind speed, involving the derivation of an appropriate model structure and parameters based on the collected data.

Initially, the stationarity of the time series data is evaluated utilizing the autocorrelation function (ACF) and running order charts. These visual aids assist in scrutinizing trends within the data and validating the assumption of constant variance. Sequential differencing of the data series is conducted based on the observed characteristics in the ACF and PACF plots until stationarity is confirmed [46].

Subsequently, the autoregressive (AR) and moving average (MA) terms are determined using the ACF and PACF plots. These graphical representations aid in the selection of the AR and MA variables for the model [47].

Initially, the stationarity of the time series data is evaluated utilizing the autocorrelation function (ACF) charts. The ACF chart in Figure 5 displays values ranging from a maximum of 1.0 to a minimum of -0.2 for lag values between 0 and 4, indicating a moderate level of autocorrelation. Sequential differencing of the data series is conducted based on the observed characteristics in the ACF plots until stationarity is confirmed.

Subsequently, the autoregressive (AR) and moving average (MA) terms are determined using the ACF charts. These graphical representations aid in the selection of the AR and MA variables for the model. This process ensures the accurate modeling and prediction of wind speed [47].

The series depicted in Figure 6 exhibits clear and regularly recurring cyclical activity, suggesting potential regularity within the underlying processes of interest. Understanding these processes could be facilitated by examining the speed or frequency of the oscillations observed in the main series.

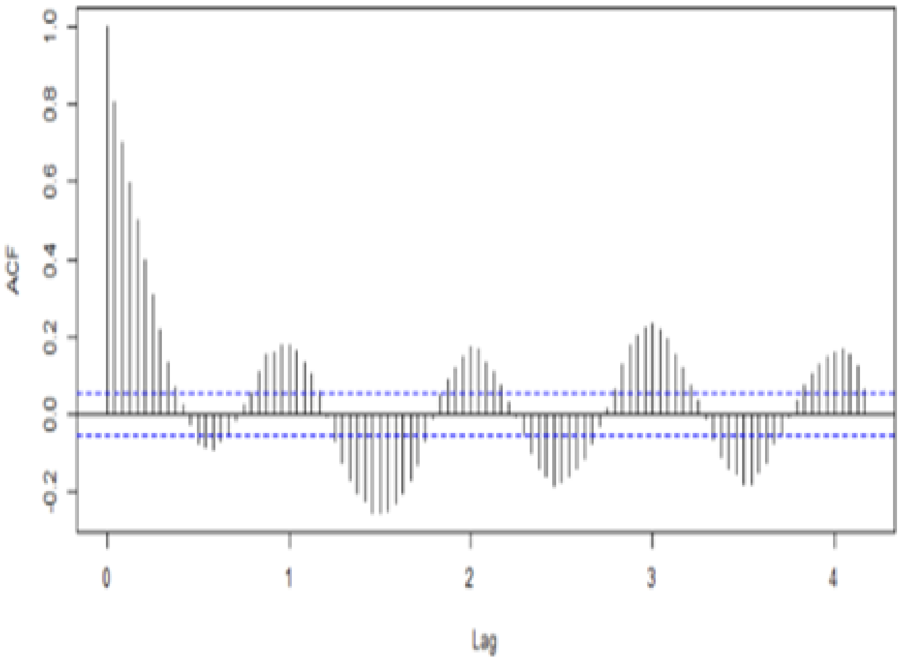


Figure 5. Functions of autocorrelation for observed wind speed data.

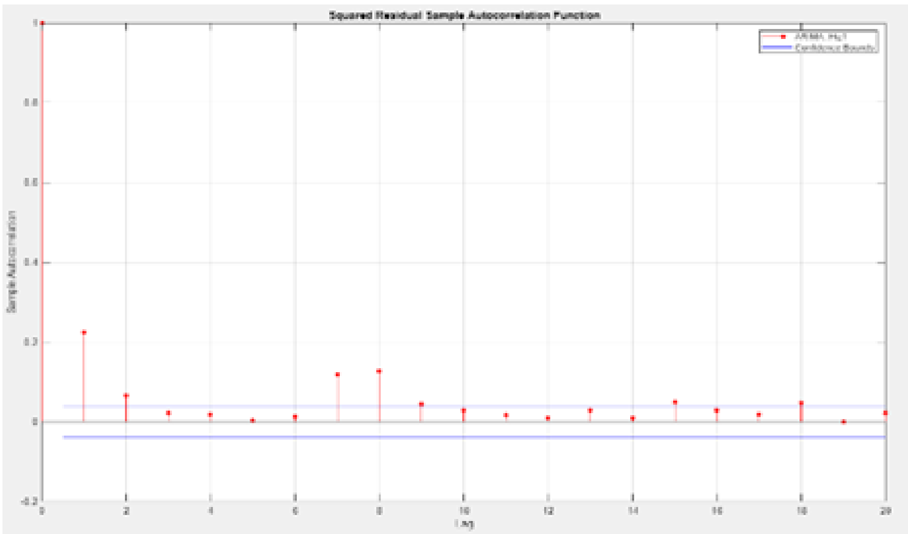


Figure 6. Functions of partial autocorrelation for data on measured wind speed.

Two primary types of variations are evident in the series. Firstly, there are distinct sinusoidal fluctuations characterized by dips and peaks. Secondly, there are periodically repeated fluctuations occurring at a slower frequency.

Non-stationary data are typically unpredictable and challenging to model. However, the periodic behavior observed in this series suggests the possibility of achieving stationarity. Techniques such as differencing can be employed to eliminate the effects of periodicity from the data [48].

Time series exhibiting frequent cycles and repetitive activity are more straightforward to comprehend and model. This implies that the underlying processes may possess regularity, distinguishable by the frequency or speed of oscillations defining the behavior of the parent series.

Non-stationary time series may yield inaccurate results, potentially indicating a lack of correlation between variables. Transforming non-stationary data into stationary data is crucial for obtaining consistent and reliable findings.

A stationary process consistently reverts to its long-run mean and maintains a constant variance over time. Conversely, a non-stationary process lacks these characteristics, exhibiting variable variance, a non-converging mean, or a lack of return to its long-run mean over time.

The gradual decline in autocorrelation function (ACF) values suggests non-stationarity in the data. Thus, transforming the data into a stable series is necessary to arrest the decline of ACF values [46].

4.2. Prediction model LSTM

Constructing an LSTM regression network involved specifying an LSTM-RNN layer with training options [34]. Multiple initial learning rates were tested to identify the optimal training parameter that yielded the lowest RMSE and loss, specifically at a learning rate of 0.01. Figure 7 illustrates how the initial learning rate affects training time, showing an increase in training time as the learning rates decrease. However, achieving the best outcome may pose challenges with a limited number of iterations. A high learning rate can expedite training but may result in divergence or failure to converge if excessively high. Moreover, substantial weight changes may enhance improvement but could also degrade the loss function. Through experimentation with different initial learning rates, a 24-step prediction was conducted during time step testing, resulting in improved training outcomes and a reduction in function loss to a manageable level. These findings underscore the efficacy of LSTM for large time series datasets and highlight the effectiveness of the specified model in minimizing RMSE.

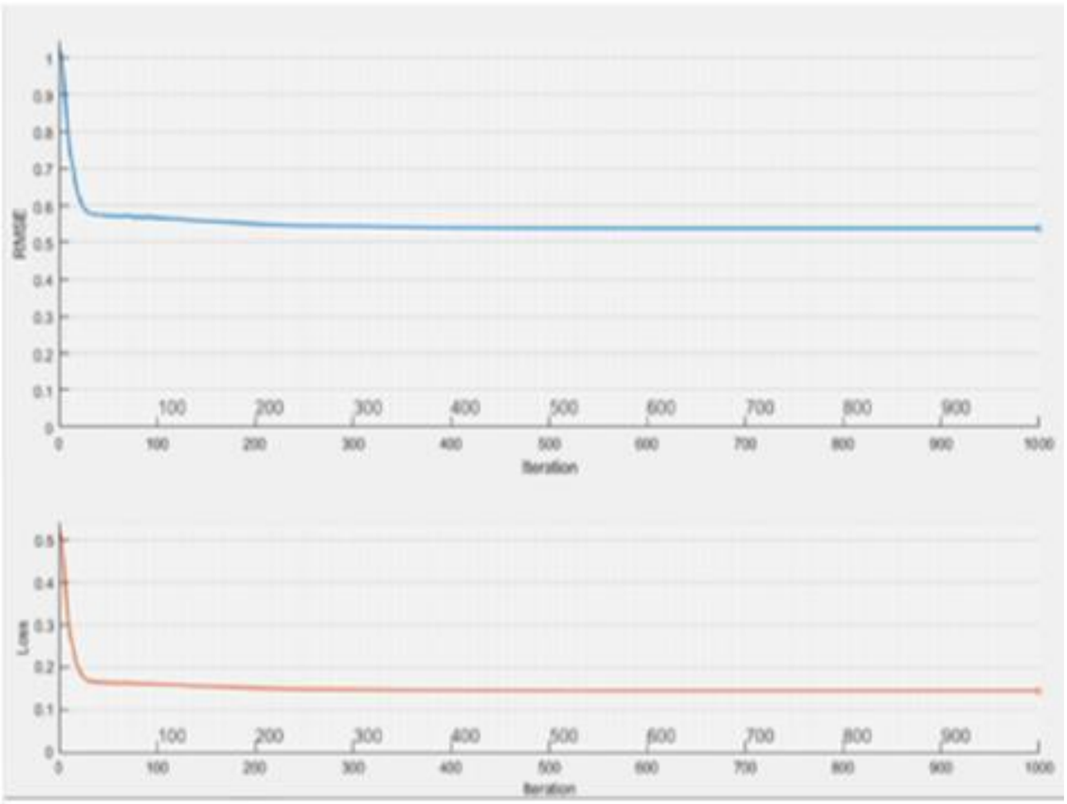


Figure 7. Process of training as learning rate of 0.01 and time step test of 24.

During LSTM-RNN training, the hidden layer receives feedback from the anticipated values of the preceding phase [34]. Throughout the validation process, the model is fine-tuned to fit all of the training data and then updated after each prediction. In this scenario, before generating the subsequent forecast, the model undergoes two additional training cycles. The prediction is then normalized using the previously determined mean and standard deviation, after which the RMSE is computed [35].

The 24-step wind speed forecast results are displayed in Figure 8. It can be observed that there are no noticeable oscillations, and all of the model's training epoch forecast data closely resemble the actual data. Furthermore, the model's total test RMSE score is the lowest, indicating uncommon occurrences of vanishing gradients and gradient bursts for the LSTM algorithm. Moreover, the expected outcomes show no significant deviation, falling within a reasonable range.

Both the ARIMA and LSTM models' outputs are assessed based on two key metrics: MAE and RMSE. These metrics provide insight into the accuracy and precision of the forecasts generated by each model. By comparing the performance of the ARIMA and LSTM models using these metrics, we can determine which model is more effective in predicting wind speed.

Upon analyzing the results presented in Table 2, it becomes evident that the LSTM model outperforms the ARIMA model in terms of efficiency. This suggests that the LSTM model is better able to capture the underlying patterns and dynamics in the wind speed data, resulting in more accurate and reliable forecasts compared to the ARIMA model.

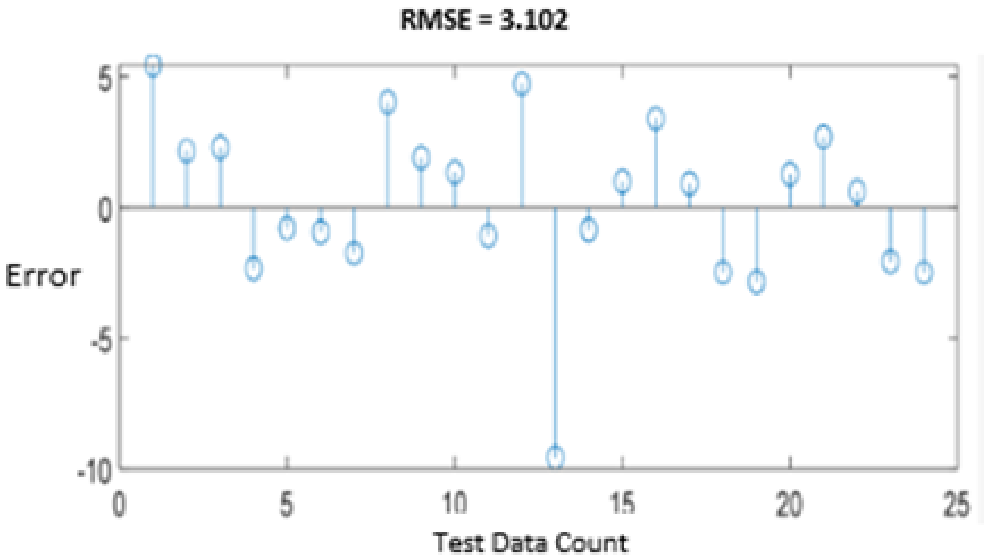


Figure 8. RMSE outcome in 24-step stages.

Table 2. Summary of statistical errors of the test data.

Model	RMSE	MAE
ARIMA	3.312	2.682
LSTM	3.102	2.235

The comparison between the ARIMA and LSTM models reveals important insights into their forecasting performance. Specifically, the MAE and RMSE values offer a quantitative assessment of the accuracy of the forecasts generated by each model.

For the ARIMA model, the MAE value is calculated to be 2.682, while the RMSE value is 3.312. In contrast, the LSTM model achieves a lower MAE value of 2.235 and a lower RMSE value of 3.102. These figures clearly indicate that the LSTM model outperforms the ARIMA model in terms of forecast accuracy.

The RMSE metric measures the degree of deviation between the expected and actual values, while the MAE metric quantifies the average discrepancy between the true and predicted values. By evaluating both metrics, we gain a comprehensive understanding of the forecast accuracy. In this comparison, the LSTM model exhibits a lower RMSE value compared to the ARIMA model, indicating that its predictions are closer to the actual values. Additionally, the LSTM model achieves a lower MAE value than the ARIMA model, further highlighting the improved accuracy of its forecasts.

Figure 9 illustrates the 24-step prediction results of wind speed time series data, presenting the predictions produced by the LSTM deep learning model alongside the observed values.

Upon analysis of the graphs, it becomes apparent that the LSTM model's predictions closely track the observed values. Specifically, when the observed values decrease, the LSTM prediction values also decrease, indicating the model's ability to accurately identify trend changes in time series data. Likewise, when the observed values increase, the LSTM prediction values also increase, demonstrating the model's capability to detect seasonal changes in the data.

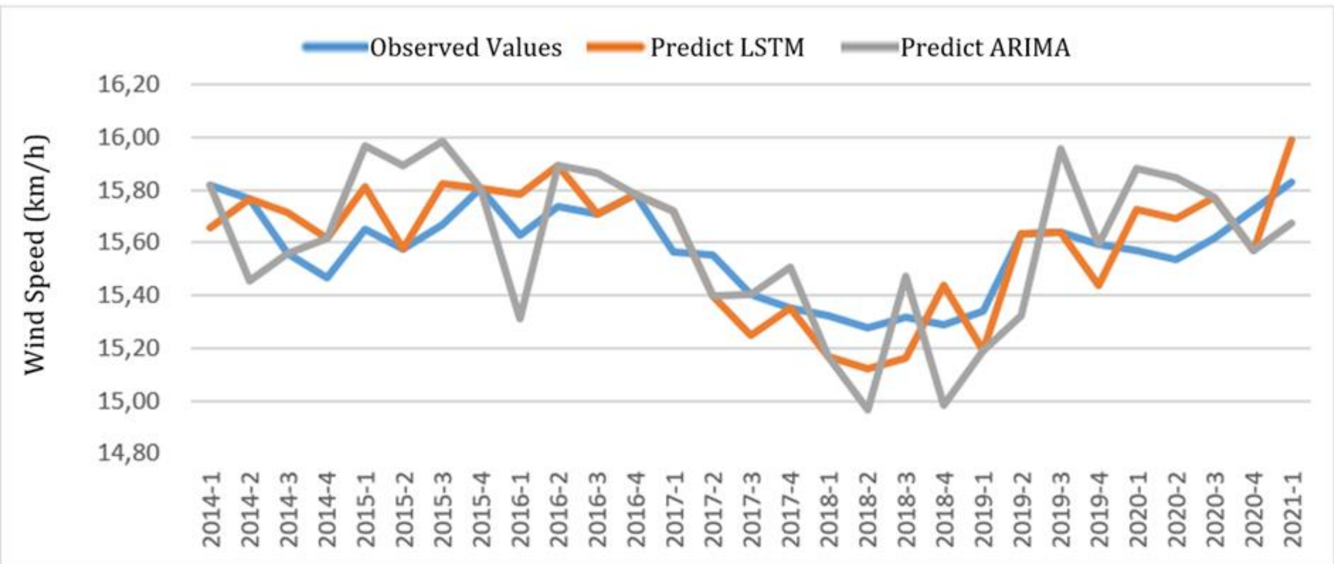


Figure 9. Using ARIMA and LSTM models, compare the three-month average wind speed data.

While the ARIMA model also yields results close to the predicted values, it exhibits discrepancies in trend detection. Notably, instances where the actual values increase are accompanied by decreases in the prediction values from the ARIMA model, despite achieving a lower error rate compared to the LSTM model. This suggests that the ARIMA model may struggle to accurately identify trend changes in time series data.

In conclusion, the graph in Figure 9 underscores the superior effectiveness of the LSTM deep learning model in wind speed prediction. Leveraging its ability to discern trends and seasonal patterns in time series data, the LSTM model produces more precise forecasts compared to the ARIMA model.

5. Discussion

Researchers from diverse fields are increasingly adopting advanced machine learning techniques, particularly deep learning algorithms. It is imperative to comprehensively evaluate the effectiveness and robustness of these modern methods in comparison to traditional approaches [49]. This study focuses on assessing the performance of two models with a specific emphasis on the Gelibolu district of Çanakkale province: a deep learning-based algorithm, the LSTM model, and a classical algorithm, the ARIMA model. A review of the literature suggests that the ARIMA model may yield superior results with limited data, as observed in previous academic research. However, the substantial amount of data utilized in the models developed for this study indicates that LSTM and other deep learning-based algorithms outperform traditional techniques like ARIMA. This underscores the significant potential of deep learning algorithms and approaches, particularly in forecasting complex time series data such as wind speed.

In addition to model performance, it is important to acknowledge the challenges and limitations encountered during the course of this research. Data availability, model selection, parameter tuning, and computational resources posed significant challenges throughout the study. Despite these challenges, the findings of this research provide valuable insights into the effectiveness of deep learning techniques in wind speed prediction. Future research endeavors should explore the application of deep learning techniques to other forecasting problems within the domain of wind speed prediction. Additionally, a more detailed examination of the performance of deep learning techniques across different datasets could provide valuable insights into this research area.

6. Conclusion

The results of this study demonstrate that the LSTM model outperforms the ARIMA model in predicting average wind speed in the Gelibolu district of Çanakkale province. With an average RMSE of 6.3% and MAE of 16.67%, the LSTM-based algorithm exhibits greater accuracy compared to ARIMA, highlighting its effectiveness in forecasting time series data.

The findings of this research emphasize the advantages of utilizing deep learning algorithms, particularly LSTM, in wind speed prediction. Despite previous studies suggesting superior performance of ARIMA with limited data, our results indicate that the abundance of data used in this study favors LSTM and other deep learning-based techniques.

Future research directions may involve exploring the application of deep learning methodologies to additional forecasting challenges within the realm of wind speed prediction. Further investigation is warranted to ascertain the extent of improvement achievable through deep learning approaches across diverse datasets with varying features.

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Author contributions

Adem Demirtop: Data analysis, drafting the manuscript. **Onur Sevli:** Defining the methodology, evaluating the results and editing the draft.

Conflicts of interest

The authors declare no conflicts of interest.

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